



DATA MINING ANALYSIS ON AERODYNAMIC STEALTH DESIGN PRINCIPLES OF AIRFOIL PROFILES

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Abstract

In the multidisciplinary design of aerodynamic stealth for airfoil profiles, the diversity and coupling relationships among objectives and variables increase the computational cost and development cycle of the optimization design. This paper focuses on data mining using two types of algorithms: random forest and isometric mapping. The data mining considers many objectives: aerodynamic lift coefficient, drag coefficient, and lift-to-drag ratio, as well as vertical polarized radar cross-section and horizontal polarized radar cross-section. In the analysis of objectives and design variables, the aerodynamic and stealth performance of the airfoil profiles are greatly influenced by the curvature of the leading and trailing edges, followed by the chord length. Larger curvature of the leading edge reduces drag and improves stealth performance. Smaller curvature of the trailing edge improves the lift coefficient, lift-to-drag ratio, and stealth performance. Through data mining, specific reference ranges for design variables are provided to obtain airfoil profiles with superior aerodynamic stealth performance.

Keywords: aerodynamic stealth design; data mining; random forest; iso-metric mapping

1. General Introduction

Aerodynamic stealth integrated design plays a guiding role in the exterior design of fighter jets. However, one of the challenges in aerodynamic stealth multidisciplinary design optimization is the complex interactions among a large number of objective functions, design variables, and constraints [1][2]. Duan et al. [3] used the Proper Orthogonal Decomposition (POD) algorithm as a surrogate model to reduce computational costs, employing the Genetic Algorithm (GA) to identify the range of the global optimal solution. Li et al. [4] established a reinforcement learning-based predictive surrogate model for wing drag and pressure distribution, learning the strategy for reducing transonic wing drag through the Proximal Policy Optimization (PPO) algorithm. Chong et al. [5] employed an Artificial Neural Network to build a data-driven surrogate model for predicting the aerodynamic characteristics of wing configurations, utilizing the GA to search for optimized wing shapes. It is evident that faced with high-dimensional, multi-objective problems, traditional surrogate model methods first fit sample data to predict the aerodynamic performance of new shapes and then perform multi-objective optimization under multiple constraints using optimization algorithms. However, the established surrogate models lack further exploration of the sample data obtained through extensive computational resources, which actually contains important features such as the significance of design variables and the correlation between objective functions, waiting for further exploration and utilization for guiding optimization designs [6].

There is a rich variety of methods in data mining, including Random Forest [7], Adaptive Boosting Ensemble Algorithm [8], Isometric Mapping [9], Self-Organizing Map [10], and suitable data mining methods can effectively extract the relationship between objective functions and design variables. Rational reduction of the design space [11] benefits designers in focusing more on exploring the most potential design space to improve design efficiency. Additionally, it helps eliminate design choices that do not meet specific requirements, thus reducing computational and resource costs, saving time, and enabling designers to more fully consider the impact and interaction of design

variables to optimize design quality. Oyama et al. [12] decomposed surface pressure data of Pareto optimal solutions for transonic wing profiles using the POD method, finding that in low drag wing designs, lift increase depends on changes in wing trailing edge curvature. Kanazaki et al. [13], through variance analysis, discovered that the thickness on the upper surface and the sweep back angle are crucial parameters affecting drag coefficients under transonic/subsonic conditions.

In terms of the impact of design variables on design objectives, Random Forest can quantitatively represent, while Isometric Mapping can qualitatively represent. Therefore, by using these two data mining algorithms, design rules in the aerodynamic stealth optimization process for wing profiles can be extracted. The second part of this paper mainly introduces relevant issues in aerodynamic stealth optimization for wing profiles. The third part covers data mining theory and its model architecture, while the fourth part focuses on knowledge extraction for optimization design based on data mining methods. Finally, the paper concludes in the fifth part.

2. Airfoil Aerodynamic Stealth Optimization Problem

2.1 Design Objectives

This paper conducts data mining research around the two core issues of airfoil aerodynamic stealth. Specifically, two flight states, $H=0\text{km}$ 、 $Ma=0.2$ 、 $\alpha=8^\circ$ and $H=12\text{km}$ 、 $Ma=0.8$ 、 $C_L=0.4$, are selected as design objectives:

1) Maximize lift-to-drag ratio, i.e., the objective function is as follows:

$$K = C_{L/D}^{\text{subsonic}} \quad (1)$$

2) Maximize lift, i.e., the objective function is as follows:

$$C_L = \frac{L}{\frac{1}{2}\rho V^2 S} \quad (2)$$

3) Minimize drag, i.e., the objective function is as follows:

$$C_D = \frac{D}{\frac{1}{2}\rho V^2 S} \quad (3)$$

where S is the reference area, $\bar{c}$ is the average aerodynamic chord length used as the reference length.

4) Minimize radar cross-sectional area, i.e., the objective function is as follows:

$$RCS = 4\pi \lim_{R \rightarrow \infty} R^2 \frac{|H^s|^2}{|H^i|^2} = 4\pi \lim_{R \rightarrow \infty} R^2 \frac{|E^s|^2}{|E^i|^2} \quad (4)$$

Where the superscript s indicates the scattering field, i indicates the incident field, H indicates the magnetic field, E indicates the electric field, and R indicates the distance from the target to the radar receiver. The incident wave polarization modes are vertical polarization wave (TE) and horizontal polarization wave (TM).

2.2 Design Variables and Definitions

Based on NACA65(3)-014 airfoil data, this paper employs the Latin hypercube and perturbation CST parameterization method [14] to obtain a large training sample, aiming to maximize the model's generalization ability. Ultimately, a dataset containing 5000 two-dimensional airfoils is obtained.

The CST basic function is expressed as follows:

$$B(x) = C(x) \cdot S(x) \quad (5)$$

Where the class function $C(x) = x^{N_1} \cdot (1-x)^{N_2}$ defines the geometric shape. For airfoils with blunt leading edges and pointed trailing edges, N_1 and N_2 are chosen as the feature parameters of the class function, with values of 0.5 and 1, respectively. The shape function $S(x) = \sum_{i=0}^N A_i S_i(x)$ is used to describe the detailed geometric features based on the class function, with the basic function commonly expressed as $S_i(x) = \frac{N!}{i!(N-i)!} x^i \cdot (1-x)^{N-i}$. Figure 1 illustrates the impact region of 10 weight

coefficients A_i when $N=4$. Table 1 provides the range of variation for the weight coefficients A_i , defining them as design variables. Figure 2 illustrates the range of airfoil values based on perturbation CST.

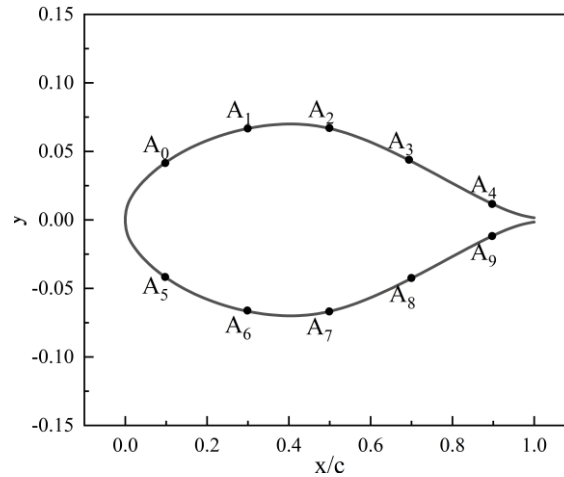


Figure 1 Parameters of 4rd CST.

Table 1 Design variables and disturbance range

Variable number	Variable	Original value	Disturbance range of value
A0	A_0	0.3424	$[-0.1, 0.1]$
A1	A_1	0.4398	$[-0.2, 0.2]$
A2	A_2	0.2418	$[-0.25, 0.25]$
A3	A_3	0.4284	$[-0.2, 0.2]$
A4	A_4	0.3162	$[-0.1, 0.1]$
A5	A_5	-0.3424	$[-0.1, 0.1]$
A6	A_6	-0.1657	$[-0.2, 0.2]$
A7	A_7	-0.3835	$[-0.25, 0.25]$
A8	A_8	-0.0838	$[-0.2, 0.2]$
A9	A_9	-0.2851	$[-0.1, 0.1]$

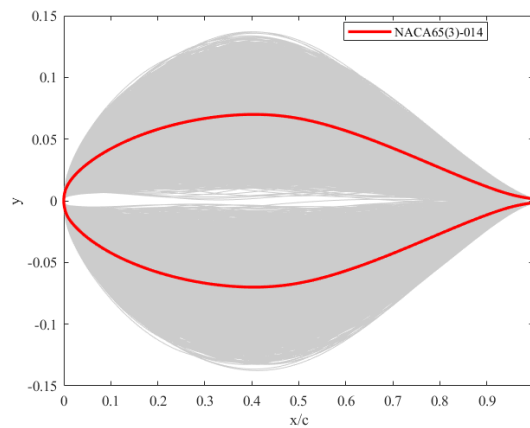


Figure 2 The airfoil profiles range based on perturbation CST.

2.3 Aerodynamic Stealth Performance Analysis Method

The accuracy of aerodynamic characteristic calculations determines the reliability of aerodynamic design results. In this paper, a self-developed Computational Fluid Dynamics (CFD) solver is employed to compute the aerodynamic performance of airfoils. The specific process involves using Reynolds-Averaged Navier-Stokes (RANS) equations for flow field control, the Spalart-Allmaras (S-A) turbulence model to close the equation set, Roe scheme for spatial discretization, and LU-SGS

implicit format for time advancement.

The stealth performance parameters of the airfoil are calculated through a self-developed method based on the moment method. The moment method, based on a rigorous theoretical model, can handle conductors and media of arbitrary shapes, making it suitable for electromagnetic problems with wide bandwidths, multiple modes, and complex structures. According to linear space theory, the integral physical operator equation for the electromagnetic field can be expressed as $L(x) = b$, where x is the unknown induced current, b is the known excitation source, and L is a linear operator. The steps for solving this operator equation using the moment method are as follows:

- (1) Select basis functions $\{j_i\}_{i=1}^N$ to describe the induced current, i.e., $x = \sum_{i=1}^N a_i j_i$;
- (2) Choose weighting functions t_j and take the inner product of the operator equation, yielding
$$\sum_{i=1}^N a_i \langle t_j, L(j_i) \rangle = \langle t_j, b \rangle;$$
- (3) Solve for the unknowns $[a]$ using an iterative method;
- (4) Substitute the solved induced current into the electromagnetic field integral equation to obtain the scattered field.

3. Data Mining Methods

3.1 Random Forest (RF)

Random Forest, proposed by Breiman [15] in 2001, is an ensemble learning method that combines the results of multiple decision trees through voting to make a final decision. It effectively reduces the risk of overfitting in individual decision trees while demonstrating high accuracy and generalization. The Random Forest model is based on the Bagging algorithm, where multiple decision trees are combined in a certain way. In each iteration, samples are randomly selected from the dataset, and a random subset of features is chosen as input. In classification problems, the majority classification result is selected as the final outcome. The schematic diagram is shown in Figure 3.

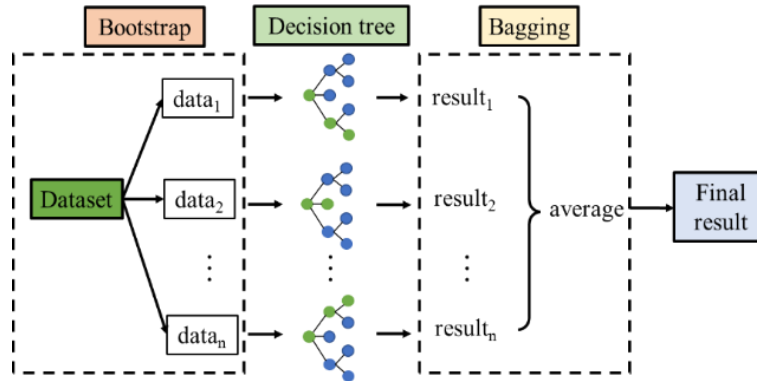


Figure 3 Schematic diagram of random forest.

The basic process of a Random Forest is as follows:

- 1) Use the Bootstrap method to split the dataset into n subsets for classification/regression;
- 2) Randomly select features from the dataset and build a decision tree using the best splitting attribute as a node;
- 3) Repeat the above two steps multiple times to create multiple decision trees;
- 4) Form a Random Forest and determine the final result through a voting process.

3.2 Isometric Mapping (Isomap)

As an extension of Multidimensional Scaling (MDS) algorithm, identifies the neighbors of each point based on Euclidean distance. It then constructs a neighborhood connectivity graph, where

connected links exist between neighboring points, and no links exist between non-neighboring points. Consequently, the problem of calculating geodesic distances between two points transforms into determining the shortest path between them on the neighborhood connectivity graph. Figure 4 illustrates the reduction from a three-dimensional data space (left) to a two-dimensional data space (right) through Isomap.

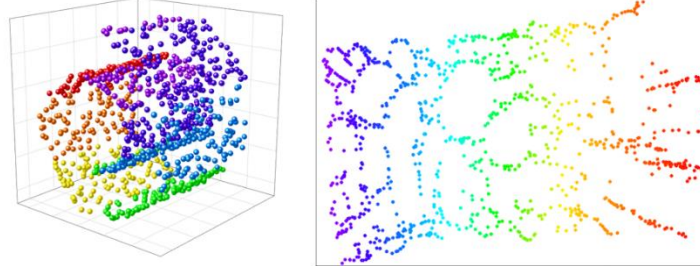


Figure 4 Dimension reduction of data by Isomap.

The basic process of Isomap is as follows:

- 1) Determine the k -nearest neighbors of sample point x_i , setting the distances between x_i and its k -nearest neighbors as the Euclidean distance, and distances to other points as infinitely far;
- 2) Use the shortest path algorithm to compute the distances $dist(x_i, x_j)$ between sample points;
- 3) Use the obtained distances $dist(x_i, x_j)$ as input for the MDS algorithm to obtain the mapping of the sample set in a lower-dimensional space.

4. Optimization Design Knowledge Extraction

4.1 Analysis of Important Design Variables for Optimization Objectives

In the construction process of a random forest, different design variables can be obtained to quantitatively assess their impact on the optimization objectives. Since the hyperparameters of the model can influence its accuracy, the range of the number of decision trees is set to [1, 1000], and the range of maximum depth is set to [1, 100]. The grid search algorithm is employed to determine the optimal hyperparameters during model training, resulting in a final decision tree count of 100 and a maximum depth of 20, with a model prediction accuracy of 98%. Figure 5 provides a visualization of the importance obtained through the random forest, where yellow indicates higher importance, and light blue indicates lower importance.

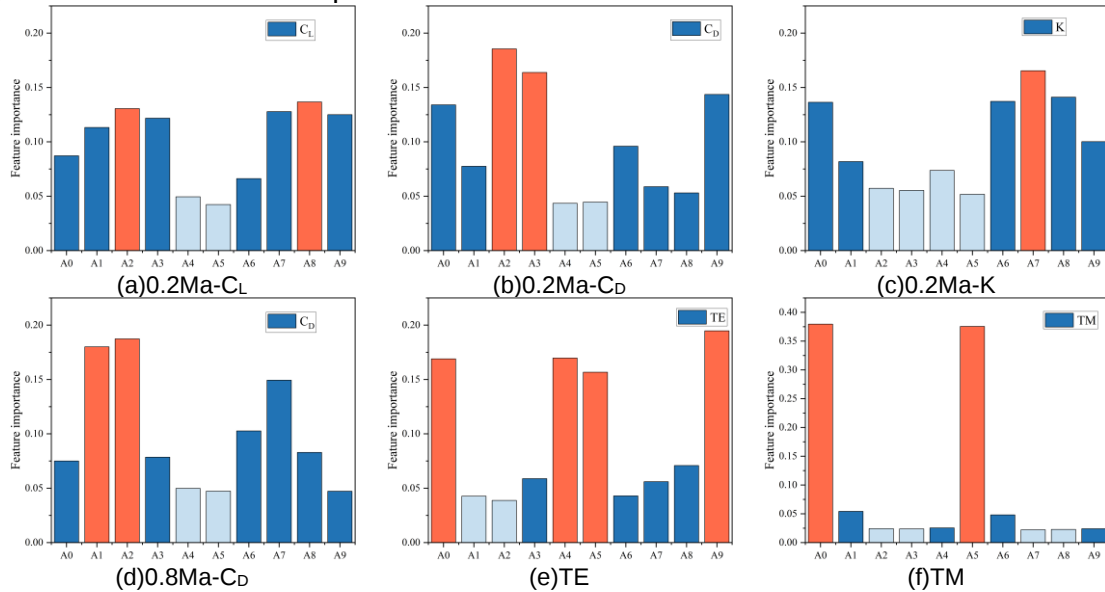


Figure 5 Order of importance of design variables obtained by random forest.

From Figure 5, it can be observed that, for the lift coefficient (C_L) at the 0.2 Mach design state, the most influential design variables are A8 and A2, followed by A9, representing the trailing edge of the airfoil. A smaller trailing edge curvature can enhance the aerodynamic efficiency of the airfoil,

reducing the generation of wake vortices and turbulence. Regarding the drag coefficient (C_D) at the 0.2 Mach design state, the most critical design variables are A2 and A3, indicating that the curvature radius of the airfoil leading edge is a significant design variable. A curved leading edge can disperse radiation and scattering signals in different directions, contributing to smoothing the surface of the airfoil and eliminating sharp edges.

At the 0.8 Mach design state, the most important design variables are A1 and A2. Similarly, for the horizontal polarization TM wave incident radar cross-sectional area, considering a $\pm 30^\circ$ sector as the main threat area, A0 and A5 are crucial design variables. This implies that the leading edge curvature of the airfoil fundamentally determines its stealth performance. For the vertical polarization TE wave incident radar cross-sectional area, A4 and A9 also determine its stealth performance.

Based on the comprehensive analysis of design variables' impact on design objectives using random forest, it can be concluded that A0, A1, A2, A4, A5, and A9—representing the leading edge and trailing edge curvature of the airfoil—are the six crucial design variables influencing aerodynamic stealth performance. Appropriately expanding the perturbation space for these six design variables is beneficial for obtaining airfoil profiles with superior aerodynamic stealth performance.

4.2 Design Variable/Objective Coupling Relationship

For 5000 data samples, their aerodynamic stealth performance is sorted. The top 10% of the results are labeled as 'high,' while the remaining data is labeled as 'low.' Figure 6 presents the results obtained using the Isometric Mapping method, where the values of the radar cross-sectional areas for vertical polarization (TE) and horizontal polarization (TM) are processed by taking their negative values.

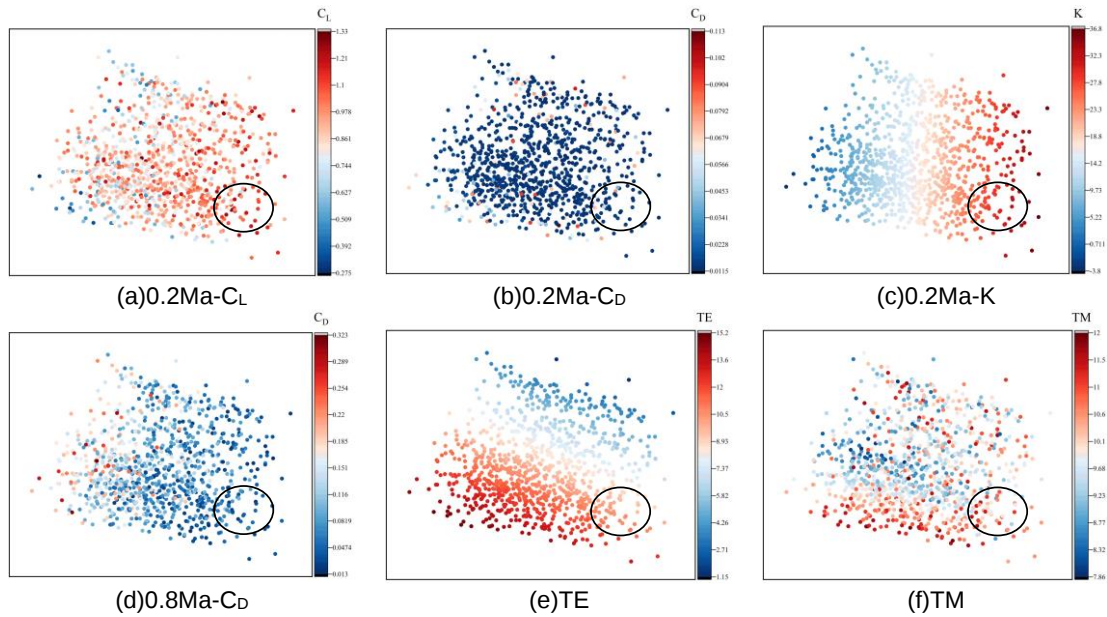


Figure 6 Objective function dyeing results of Isomap.

In Figure 6, the relationship between design objectives appears to be complex. It is evident that the regions of superior solutions for drag coefficient (C_D) at 0.2 Mach design state and 0.8 Mach design state overlap significantly, indicating good consistency between the two. Next is the lift coefficient (C_L) and lift-to-drag ratio (K) at the 0.2 Mach design state, both with superior regions located on the right side. For lift coefficient (C_L) and drag coefficient (C_D) at the 0.2 Mach design state, Isometric Mapping reveals a trade-off relationship between them, with superior lift solutions on the right and superior drag solutions on the left. The lift-to-drag ratio (K) and radar cross-sectional areas for vertical polarization (TE) and horizontal polarization (TM) show conflicting relationships across most regions, except for some overlap in the lower right part. Furthermore, Isometric Mapping clearly illustrates the differences in the distribution of lift-to-drag ratio (K) and radar cross-sectional area for vertical polarization (TE), with K showing a left-right distribution and TE showing an up-down distribution. From the analysis of aerodynamic stealth design objectives for the airfoil, the following conclusions can be drawn: It is challenging to find a solution that simultaneously optimizes all six design objectives, requiring compromise and trade-offs. At the 0.2 Mach design state, it is essential to ensure the airfoil has a high lift coefficient to meet takeoff conditions while also possessing good

cruise efficiency and stealth performance at the 0.8 Mach design state. Using the Isometric Mapping method, the region indicated by the black circles in Figure 6 can be visually identified as the decision data point area that is relatively superior when considering all six design objectives comprehensively.

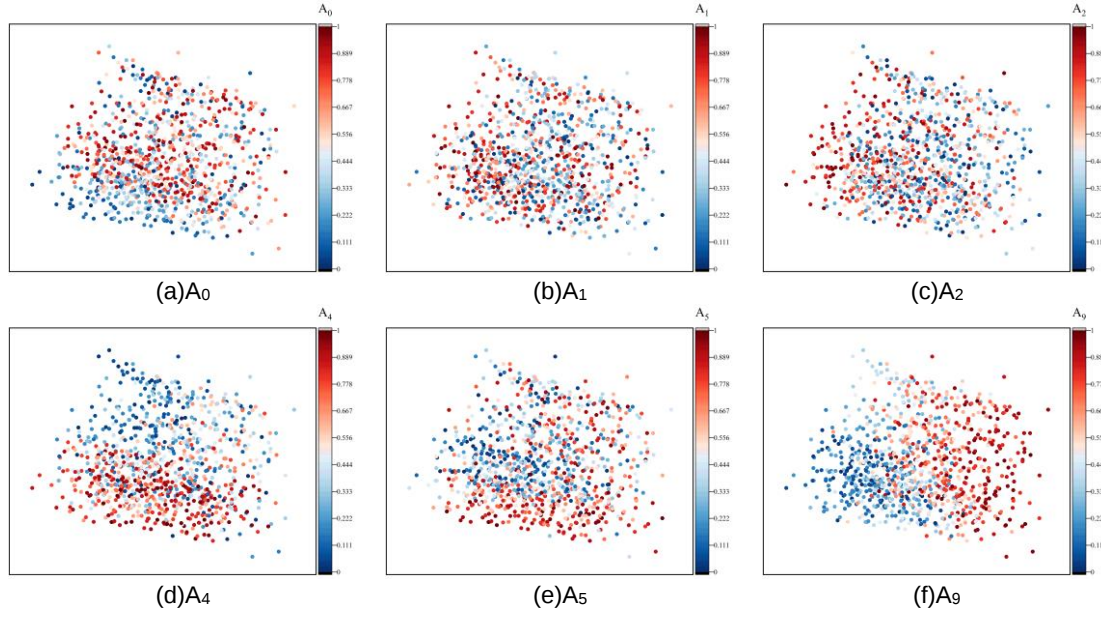


Figure 7 Design variable staining results for Isomap.

Figure 7 presents the results obtained by coloring different design variables based on their significant impact on design objectives. Contrasting the distribution of design variables with that of design objectives allows us to discern patterns in the influence of design variables on design objectives. At the 0.2 Mach design state, there is a strong positive correlation between the lift coefficient (C_L) and design variable A_9 . This implies that a smoother lower surface of the airfoil's trailing edge leads to a higher lift coefficient. For the lift-to-drag ratio (K) at the 0.2 Mach design state, there is a strong positive correlation with design variable A_9 , consistent with the relationship observed for the lift coefficient (C_L).

The distribution of values for the radar cross-sectional area for vertical polarization (TE) is strongly positively correlated with design variables A_4 and A_5 , representing the curvature radius of the airfoil's leading edge. This indicates that better stealth performance is achieved when the leading edge curvature is larger. Concerning the radar cross-sectional area for horizontal polarization (TM), its values are influenced by factors consistent with those affecting the radar cross-sectional area for vertical polarization (TE), demonstrating good consistency.

In summary, the Isometric Mapping method not only provides an intuitive understanding of the trade-off relationships between objective functions but also, compared to the random forest method, reveals patterns in the influence of design variable magnitudes on design objectives.

4.3 Design Rule Summary Analysis

Through the use of the random forest algorithm, design rules can be easily extracted. For airfoil design and optimization, the range of design variables affects the final design outcome of the airfoil profiles. Reducing the design space of non-critical design variables can effectively improve design efficiency. Figure 8 provides partial results of the design knowledge decision tree for the high lift coefficient C_L under the 0.2 Mach design condition. Further extraction of design knowledge yields the value space of design variables for airfoil profiles with a higher lift-to-drag ratio, as shown in Table 2.

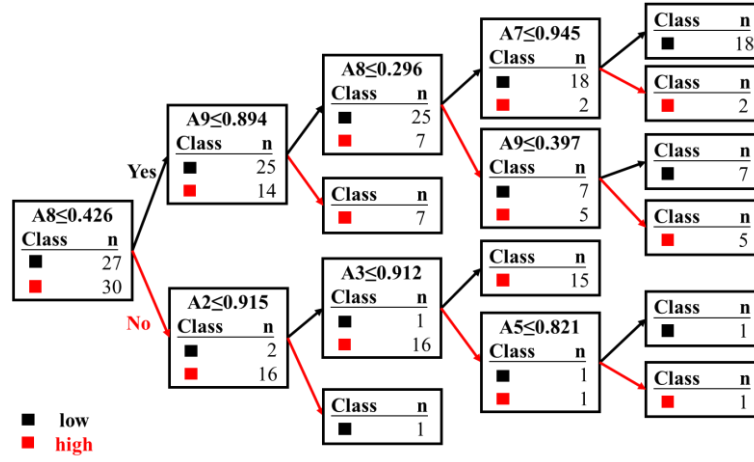


Figure 8 Design knowledge decision tree for 0.2Ma- C_L .

Table 2 Design rules of 0.2Ma- C_L

Rules	Number of data
$A0((0.231, *))$ and $A1((*, 0.729])$ and $A2((0.328, *))$ and $A4((0.318, *))$ → high	20
$A7((0.725, *))$ and $A9((0.498, *))$ and $A3((0.597, *))$ and $A8((*, 0.729])$ → high	13
$A1((*, 0.402])$ and $A9((0.866, *))$ and $A7((0.429, *))$ → high	8

From Table 2, it can be observed that there are a relatively larger number of superior solutions obtained by observing Rule 1. Therefore, Rule 1 holds higher importance in the design process. Under the conditions where design variable A0 is greater than 0.231, A1 is less than 0.729, A2 is greater than 0.328, and A4 is greater than 0.318, there is a high probability of achieving a higher lift coefficient. This aligns with the importance conclusions drawn from the random forest. Similarly, important design rules applicable to other design objectives can be derived, as shown in the table below. Table 2 to Table 7 provide parameter values for 10 normalized CST perturbations based on the initial NACA64(3)-014 airfoil profiles.

Table 3 Design rules of 0.2Ma-K

Rules	Number of data
$A6((0.842, *))$ and $A9((0.716, *))$ and $A2((0.294, *))$ and $A8((*, 0.585])$ → high	12
$A4((0.872, *))$ and $A9((0.931, *))$ and $A7((0.322, *))$ → high	9

Table 4 Design rules of 0.2Ma- C_D

Rules	Number of data
$A7((0.703, *))$ and $A6((*, 0.952])$ and $A0((0.53, *))$ and $A1((0.16, *))$ → high	31
$A2((*, 0.319])$ and $A9((*, 0.307])$ and $A6((0.714, *))$ → high	7

Table 5 Design rules of 0.8Ma- C_D

Rules	Number of data
$A6((0.582, *))$ and $A8((*, 0.984])$ and $A1((*, 0.041])$ and $A9((0.171, *))$ → high	9
$A6((0.582, *))$ and $A8((0.984, *))$ → high	5

Table 6 Design rules of TE

Rules	Number of data
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A4((0.848, *)) and A3((0.528, *)) and A6((0.428, *))	→high	24
A4((0.848, *)) and A3((0.528, *)) and A6((*, 0.428]) and A5((0.221, *))	→high	15
Table 7 Design rules of TM		
Rules		Number of data
A1((0.05, *)) and A0((*, 0.125]) and A5((0.646, *)) and A2((0.061, *))	→high	13
A1((*, 0.05]) and A8((*, 0.551]) and A5((*, 0.695])	→high	7

Table 2 to Table 7 provide quantified design rules for the lift-to-drag ratio under the 0.2 Mach design condition, drag coefficient, drag coefficient under the 0.8 Mach design condition, vertical polarized radar cross-section (RCS), and horizontal polarized radar cross-section (RCS), respectively. These design rules can be utilized not only to narrow down the value space of design variables during the optimization phase, thereby enhancing design efficiency, but also to offer valuable insights for future airfoil design endeavors.

5. Summary

This paper takes the example of airfoil design optimization and conducts data mining research on the design variables and design objectives in the aerodynamic stealth design based on two representative methods, namely, Random Forest (RF) and Isometric Mapping (Isomap). The following conclusions are drawn:

- 1) For aerodynamic stealth design of airfoil profiles, A1, A2, A5, and A9 are the most crucial design variables. Achieving a comprehensive improvement in aerodynamic stealth performance can be realized by balancing and adjusting key factors such as the leading edge and trailing edge curvature of the airfoil profiles. A smaller trailing edge curvature enhances the aerodynamic efficiency of the airfoil profiles, reducing the generation of wake vortices and turbulence. Curved leading edges disperse radiation and scattering signals in different directions, contributing to smoothing the airfoil profiles surface and eliminating sharp edges. In subsequent optimizations, appropriately expanding the value space of sensitive design variables is advantageous in obtaining airfoil profiles with superior aerodynamic stealth performance.
- 2) In the context of airfoil aerodynamic stealth, there exists a trade-off relationship between aerodynamic performance and stealth performance. Optimal solutions can be simultaneously achieved for vertical polarization and horizontal polarization. The superior solution can only be found in the favorable 0.2 Mach- C_L region, sacrificing the intermediate region of optimal vertical polarization TE radar cross-section and horizontal polarization TM radar cross-section for stealth performance.
- 3) Isometric Mapping provides a more intuitive description of design objectives, revealing the relationship between design objectives and offering a more precise insight into the primary impact characteristics of design variables on design objectives. The Random Forest algorithm not only indicates the importance of each design variable to design objectives but also provides the value range of design variables that yield superior performance airfoil profiles.

In summary, these two data mining methods have their own characteristics and advantages in extracting design rules. They can analyze design variables and objectives in airfoil optimization from different perspectives, obtaining valuable design knowledge. In practical applications, a comprehensive use of these two methods can facilitate the exploration and reuse of latent design knowledge in the aerodynamic stealth optimization of airfoil profiles.

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